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Original research article

A Comparative Study of Lot-Sizing Techniques under Fluctuating Demand

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ABSTRACT

This research aims to compare the efficiency of different lot-sizing techniques under fluctuating demand patterns. Demand was simulated using a normal distribution and categorized into two levels based on the variability coefficient (VC): low variability (VC < 0.25) and high variability (VC ≥ 0.25), across two planning horizons: 12 periods (monthly) and 52 periods (weekly). The study evaluates both the exact optimization approach using the Wagner–Whitin algorithm (WW) and various heuristic methods, including Lot-for-Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), and Part-Period Balancing (PPB). Each scenario was tested across two levels of ordering cost and five levels of holding cost. The results indicate that the WW algorithm outperformed all other techniques across all simulated scenarios by achieving the lowest total inventory management cost. Among the heuristic methods, POQ and LFL emerged as viable alternatives; their efficiency improved dramatically as holding costs increased because they align order quantities closely with actual demand, thereby reducing average inventory levels and carrying costs.

Keywords: Fluctuating demand; Heuristic; Inventory; Lot-sizing techniques; Optimization

1. Introduction

Businesses today face economic fluctuations, changing consumer behavior, and supply chain uncertainties, all of which directly affect resource management. To maintain operational efficiency and competitiveness, effective inventory management has become a crucial factor. Inventory management directly impacts operating costs, capital utilization, and the ability to meet customer demand. This is extremely important for retail businesses; therefore, determining the appropriate order quantity under uncertain demand conditions is essential. Because incorrect ordering decisions can result in either excessive inventory, leading to increased holding costs, or insufficient

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inventory, resulting in lost business opportunities and revenue [1].

Lot sizing is an important process in inventory management, with the goal of determining the optimal order quantity for each replenishment cycle to minimize overall inventory-related costs [2]. Products with volatile demand patterns require comprehensive data and appropriate analytical tools for management inventory. Relying on traditional inventory management approaches, such as fixed reorder point systems or simple linear forecasting methods, may not be sufficient to cope with the rapid changes in modern markets. Therefore, determining order quantities under conditions of non-stationary or variable demand requires specialized techniques that are flexible and adaptable to changing demand environments.

The selection of a lot-sizing method or model depends primarily on the characteristics of product demand, which can generally be divided into two types: stable demand and variable demand. When product demand remains constant and continuous throughout the planning horizon, the Economic Order Quantity (EOQ) model can be applied. This classical EOQ model was originally developed by Harris [3] to determine the optimal order quantity that minimizes total inventory management costs. However, a major limitation of the EOQ model is that it cannot accommodate variable demand conditions or situations involving changes in prices and inventory-related costs [4].

Due to the limitations of the EOQ model mentioned above, a demand variation analysis should be performed before selecting an appropriate lot-sizing method. Peterson and Silver [5] proposed using the Variability Coefficient (VC) as a criterion for classifying demand, an approach commonly known as the Peterson–Silver rule. When VC value is less than 0.25, the variability of demand is considered low, and an EOQ model can be used, employing the average demand value in its calculation. Conversely, when VC is greater than or equal to 0.25, it indicates high demand variability, and a dynamic lot-sizing approach should be used. Dynamic lot-sizing adapts to time-varying demand fluctuations to establish the most cost-effective order quantity per period [6].

Dynamic lot-sizing techniques include optimization and heuristic-based approaches. The optimization-based approach uses the Wagner–Whitin algorithm (WW) to achieve optimal solutions through mathematical programming [7-11]. There are several heuristic problem-solving methods such as the Silver–Meal (SM) method and the Part-Period Balancing (PPB) method. In addition, other heuristic lot-sizing methods can also be applied. These include static models, which determine fixed order quantities that satisfies demand for each period, such as the Lot-for-Lot (LFL or L4L) method. Another heuristic is periodic models, which determine order quantities at regular intervals, including the Period of Supply (POS) method and the Period Order Quantity (POQ) method [12-13].

Soni [14] applied and compared seven lot-sizing techniques for each product in the metal industry: Lot-for-Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), Least Total Cost (LTC), Least Unit Cost (LUC), Part-Period Balancing (PPB), and the Wagner–Whitin Algorithm (WWA). The study evaluated the impact of these lot-sizing techniques on order quantities, overall inventory management costs, reorder points, and reorder frequencies. The results demonstrated that significant cost savings could be achieved for specific products by using lot-sizing techniques instead of relying on the existing ordering system. Similarly, Mahachandra and Astri [15] analyzed material inventory planning for the construction of bored piles in a building project by applying Material Requirements Planning (MRP) in conjunction with four lot-sizing techniques, namely Lot-for-Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), and Part-Period Balancing (PPB). The objective was to identify the most suitable lot-sizing technique based on minimizing order

quantities and inventory management costs. The results indicated that the PPB method yielded the lowest inventory cost for multiplex phenolic film and ready-mixed concrete materials, whereas the POQ method produced the lowest inventory cost for three types of reinforcing steel materials. Likewise, Hendrieta [16] conducted a study to develop an efficient raw material inventory planning system aimed at reducing production lead time and inventory holding costs in furniture cabinet manufacturing. The study integrated Material Requirements Planning (MRP) with four lot-sizing techniques, including Lot-for-Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), and Part-Period Balancing (PPB). The findings revealed that the POQ method generated the lowest total inventory cost, making it the most appropriate strategy for the procurement of wood panel materials.

Ferdian and Halim [10] developed a dynamic lot-sizing (DLS) model for retailers operating with multiple suppliers, quantity discounts, and production capacity constraints, incorporating advanced demand information (ADI). The numerical studies demonstrated that ADI contributed to a reduction in total production costs and provided an effective solution for production planning problems of small and medium-sized enterprises (SMEs) and retailers that utilize demand information in advance. Similarly, Martinez-Luna et al. [11] investigated dynamic lot-sizing approaches to improve inventory management efficiency in a Mexican manufacturer of air freshener sheets. The study compared two lot-sizing methods, namely the Silver–Meal heuristic and the Wagner–Whitin algorithm, for determining order quantities of various paper-based raw materials. The results showed that the Wagner–Whitin algorithm achieved lower total inventory costs than the Silver–Meal method. These findings are consistent with those reported by Gáti and Bányai [9], who successfully applied both the Wagner–Whitin and Silver–Meal methods to Material Requirements Planning (MRP). Their study demonstrated that dynamic lot-sizing techniques can effectively support material planning decisions and generate substantial cost savings in the short term.

Dynamic lot-sizing methods have been developed for products with variable demand. From the literature reviewed above, the effectiveness of each method depends on the specific characteristics of demand patterns and inventory environments being considered. Consequently, no single lot-sizing method is universally optimal. A comprehensive analysis and comparison of dynamic lot-sizing methods under varying levels of demand variability; both high-variability and low-variability demand scenarios; would provide valuable insights into their relative efficiency. This investigation enables the selection of the optimal lot-sizing technique for inventory management under various fluctuating demand scenarios.

2. Materials and Methods

2.1 Demand data simulation

This research simulated demand data with a normal distribution, specifying number of time periods (n): monthly ($n = 12$) and weekly ($n = 52$).

To encompass different levels of demand, the Variability Coefficient (VC), which is the squared coefficient of variation, was used as an indicator of demand variability. Demand variability is classified as low when the VC value is below 0.25, and high when it reaches or exceeds 0.25 [5]. Furthermore, Dajani et al. [17] proposed a VC threshold of 0.25 to balance high data consistency with minimal data restriction, a value deemed sufficient and appropriate for this study.

Let D_t denote the demand quantity in period t. The Variability Coefficient (VC) can be calculated as shown in Eq. (2.1).

$$VC = \frac{Variance\ of\ Demand}{Square\ of\ Average\ Demand}, \quad (2.1)$$

$$VC = \frac{\frac{1}{T}\sum_{t=1}^{T}\left(D_t - \bar{D}\right)^2}{\bar{D}^2}. \quad (2.1)$$

Accordingly, this study categorized the VC into two levels:

- Low variability ($VC < 0.25$): Demand data were simulated using a normal distribution ($\mu = 100$) with standard deviations (σ) of 10 and 30.
- High variability ($VC \geq 0.25$): Demand data were simulated using the same mean ($\mu = 100$) but with larger standard deviations (σ) of 50, 70, and 100.

Combining the five demand distribution patterns with two levels of demand periods yielded ten simulation scenarios. For each scenario, 100 demand datasets were generated using Minitab 19 software. This employs a Random Number Generator (RNG) based on the Inverse Cumulative Probability Function (Inverse CDF) to generate random numbers with default random seed. These diverse scenarios help to reflect product demand patterns under conditions comparable to the real-world operating environment of an inventory management system. However, negative demand values from the simulated normal distribution were set to zero before the dataset was used for lot-sizing. The simulated dataset is then subjected to dynamic lot-sizing analysis using the QM for Windows, following the methodology described in next section.

2.2 Dynamic lot-sizing techniques

In each simulation scenario, lot-sizing methods were evaluated across two levels of ordering cost ($O = 20, 50$) and five levels of holding cost ($H = 0.1, 0.2, 0.3, 0.5, 1.0$). The order lot sizes were then determined using the following techniques:

In the case where demand is unstable and low variability ($VC < 0.25$): Five dynamic lot-sizing techniques were used, consisting of the optimization-based approach using the Wagner–Whitin algorithm (WW) and heuristic methods, including Lot-for-Lot (LFL), Economic Order Quantity (EOQ), Period Order Quantity (POQ), and Part-Period Balancing (PPB).

In the case where demand is unstable and high variability ($VC \geq 0.25$): Four dynamic lot-sizing techniques were used, consisting of the optimization-based approach by the WW algorithm and heuristic methods, including LFL, POQ, and PPB.

2.2.1 Wagner-Whitin algorithm (WW)

The Wagner–Whitin algorithm (WW), developed by Harvey M. Wagner and Thomson M. Whitin in 1958, is a mathematical programming model used to obtain the optimal solution for the lot-sizing problem [18]. Its objective is to minimize the overall cost of inventory management. The objective function of the model is presented in Eq. (2.2) and the model constraints are given in Eqs. (2.3) – (2.6) as follows:

Index:

t Period ($t = 1, 2, \ldots, T$)

Decision Variables:

Q_t Order quantity in period t

I_t Inventory level in period t

Y_t It is a binary variable equal to 1 if an order is placed in period t, and 0 otherwise.

Parameters:

O_t Ordering cost per order in period t

H_t Holding cost per unit in period t

D_t Demand in period t

M Positive large number (Big M)

Objective Function:

$$Minimize\left(\sum_{t=1}^{T} O_t Y_t + \sum_{t=1}^{T} H_t I_t\right) \quad (2.2)$$

Constraints:

$$I_{t-1} + Q_t - I_t = D_t \quad ;\forall t \quad (2.3)$$

$$Q_t \leq (M) Y_t \quad ;\forall t \quad (2.4)$$

$$I_t, Q_t \geq 0 \quad ;\forall t \qquad (2.5)$$

$$Y_t \in \{0,1\} \quad ;\forall t \qquad (2.6)$$

2.2.2 Lot-for-Lot (LFL)

Lot-for-Lot (LFL or L4L) method is an inventory planning approach in which the order quantity is set equal to the demand occurring in each period, such as monthly or weekly, as shown in Eq. (2.7). Let Q_t denote the order quantity in period t and D_t denote the demand quantity in period t

$$Q_t = D_t . \qquad (2.7)$$

The Lot-for-Lot (LFL) method eliminates inventory holding costs by aligning order quantities exactly with actual demand, thereby preventing excess stock accumulation. Consequently, this approach mitigates risks associated with material spoilage and obsolescence. However, its primary disadvantage lies in elevated ordering costs, driven by the high frequency of placements required to meet periodic demand [19-21].

2.2.3 Economic Order Quantity (EOQ)

When demand is unstable but exhibits low variability (VC < 0.25), the Economic Order Quantity (EOQ) model can be applied by using the average demand in the calculation [19] as shown in Eq. (2.8).

$$EOQ = \sqrt{\frac{2O\bar{D}}{H}}, \qquad (2.8)$$

where, EOQ is order quantity that minimizes the total cost of inventory management, $\bar{D}$ is the average demand per period, O is the ordering cost per order, and H is the holding cost per unit per period.

2.2.4 Period Order Quantity (POQ)

The Period Order Quantity (POQ) is a method to determine the lot-sizing, setting an appropriate ordering interval and calculating the order quantity for each ordering cycle. This ensures cost efficiency and reduces both ordering and holding costs. This method considers product demand within each period and incorporates the Economic Order Quantity (EOQ), as shown in Eq. (2.8), as part of the calculation. The ordering interval (p) is determined as shown in Eq. (2.9). The order lot-sizing is then set to cover the demand over the corresponding ordering cycle obtained from the calculation [22].

$$p = \frac{EOQ}{\bar{D}} . \qquad (2.9)$$

2.2.5 Part Period Balancing (PPB)

The Part-Period Balancing (PPB) method is a lot-sizing technique designed to balance inventory levels with product demand by optimizing lot sizes. Originally proposed by Joseph J. DeMatteis, its mathematical formulation was subsequently advanced by Albert G. Mendoza in 1968. The main concept of the PPB method is to adjust the order quantity (lot size) in each cycle so that the ordering cost is approximately equal to the cumulative inventory holding cost. [23, 24] The procedure of the PPB method is as follows:

1) Compute $P(t)$ which is equal to the amount of inventory held for $t = 1, 2, 3, \ldots$

$$P(1) = 0$$

$$P(2) = D_2$$

$$P(3) = D_2 + 2D_3$$

$$P(t) = D_2 + 2D_3 + \cdots + (t-1)D_t$$

When D_t is the demand quantity in period t

2) Determine the stopping point of the calculation, and the computation will be terminated when $P(t) > \frac{O}{H}$.

3) Decide the order quantity. When the condition in Step 2 is satisfied, the procedure is stopped, and the order quantity is set to cover the demand from D_1 to D_{t-1}.

4) Start the calculation again for the next period until the end of the planning horizon.

2.3 Efficiency comparison

The efficiency comparison of lot-sizing techniques is evaluated based on total ordering cost, total holding cost, and total inventory management cost (TC). The comparison was presented in the scenarios categorized by demand variability (VC) and across scenarios defined by variations in the number of time periods (n), ordering cost per order (O), and holding cost per unit per period (H).

For each scenario, a comparative analysis is performed using 100 simulated datasets based on three metrics:

1) Average cost including total ordering cost, total holding cost, and total inventory management cost.

2) The empirical frequency of achieving the lowest total inventory management cost. This is based on a total of 100 frequencies, which corresponds to 100 datasets simulating each scenario. Therefore, if a method yields the lowest total inventory management cost for each dataset, it is considered the lowest cost for that method. Thus, a method is counted whenever it produces the lowest total inventory management cost for a given dataset.

3) The cost gap between heuristics and the exact optimum for each situation was defined as percent relative change, as follows:

$$\%\,\text{Relative Change} = \frac{TC_{Heuristic} - TC_{WW}}{TC_{WW}} \times 100,$$

where, $TC_{Heuristic}$ is total inventory management cost of the heuristic method, and TC_{WW} is total inventory management cost of Wagner–Whitin algorithm.

3. Results and Discussion

3.1 Low-variability unstable demand

In the case where demand is unstable and low variability ($VC < 0.25$), demand data were simulated using the normal distributions, $N(100,10^2)$ and $N(100,30^2)$.

Dynamic lot-sizing of the first scenario, $N(100,10^2)$, $n = 12$, $O = 20$, $H = 0.1$, found that the WW method yields the lowest average total ordering cost, equal to 120.00 THB. The LFL method results in the lowest average total holding cost, equal to 0.00 THB, since each order quantity is equal to demand, therefore no inventory is carried. However, when considering the total inventory management cost, the WW method provides the lowest average total cost, equal to 179.76 THB. Thus, the WW method is the optimal method for determining order quantities in this scenario. Nevertheless, when considering only heuristic methods, the POQ method yields the lowest average total inventory management cost, equal to 212.43 THB, as shown in Table 1. The other scenarios can be analyzed and presented in a similar manner.

Table 1. Average total ordering cost, total holding cost, and total management cost of the first scenario ($N(100,10^2)$, $n = 12$, $O = 20$, $H = 0.1$).

Lot-sizing Techniques		Total Ordering Cost	Total Holding Cost	Total Management Cost
Optimization	WW	**120.00**	59.76	**179.76**
Heuristics	LFL	240.00	**0.00**	240.00
	EOQ	129.20	116.15	245.35
	POQ	125.00	87.43	212.43
	PPB	167.60	495.22	662.82

From an overall perspective, when comparing the frequency or the number of times each method yields the lowest total inventory management cost under low-variability unstable demand ($VC < 0.25$) the results are summarized in Fig. 1. It is found that, when demand is assumed to follow a normal distribution $N(100,10^2)$ and ordering cost $O = 20$ is considered, the WW method provides the lowest total cost in all scenarios. Among heuristic methods, when holding cost $H = 0.1$, the POQ method performs as the second-most method. When the holding cost $H = 0.3, 0.5, 1.0$, the LFL and POQ methods show achieve efficiency comparable to that of the WW method. When ordering cost $O = 50$,

the WW method remains the best, while LFL and POQ serve as the next best alternatives.

Furthermore, when demand follows a normal distribution $N(100,30^2)$ representing higher variability, and ordering cost $O = 20$ is considered, the WW method still yields the lowest total cost in all scenarios. Among heuristic methods, when holding cost $H = 0.1$, the POQ method again provides the second-most efficiency. When the holding cost $H = 0.5$, both LFL and POQ methods achieve substantially improved results. When $H = 1.0$, both LFL and POQ methods achieve results approaching but not fully comparable with, the WW method. When ordering cost $O = 50$, the WW method remains the best-performing approach, while LFL and POQ continue to be the second-best alternatives.

Under the same ordering cost level, when comparing demand distributions $N(100,10^2)$ and $N(100,30^2)$, it is found that the WW method yields the lowest total cost in all scenarios. However, the efficiency of heuristic methods shows a clear declining trend as demand variability increases. Therefore, it can be concluded that the WW method exhibits the highest efficiency, providing the lowest total inventory management cost in all simulation scenarios (100%). In terms of heuristic approaches, for the case of $N(100,10^2)$, at $O = 50$, when $H = 1.0$, the LFL and POQ methods perform comparably to the WW method. In contrast, for the case of $N(100,30^2)$, at $O = 50$, when $H = 1.0$, the LFL and POQ methods achieve only approximately 50% of the efficiency of the WW method. These results are consistent with the heatmap shown in Fig. 2. Moreover, when considering the average percentage of relative change between heuristics and WW algorithm, as shown in Table 2, POQ methods have the lowest value both $n = 12$ and $n = 52$, followed by LFL method.

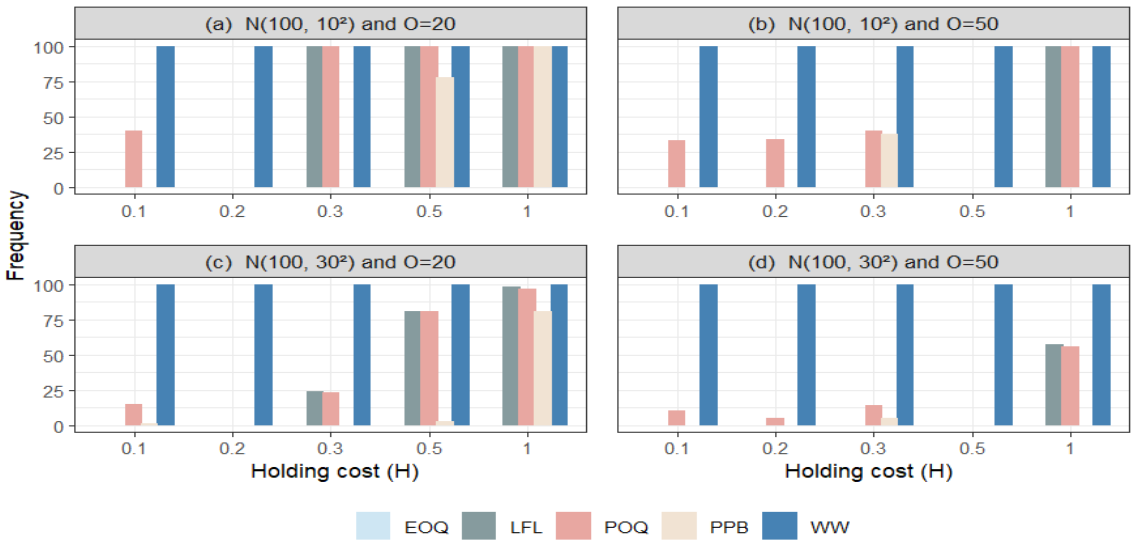


Fig. 1. Column chart the frequency that lot-sizing techniques yield the lowest total inventory management cost under low-variability unstable demand ($VC < 0.25$).

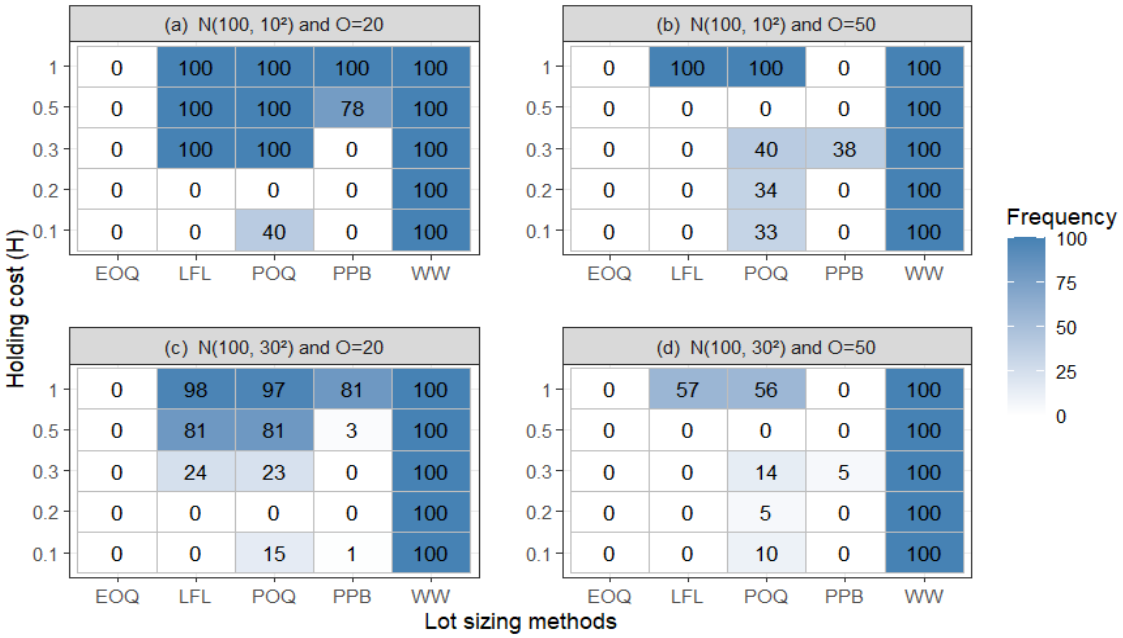


Fig. 2. Heatmap the frequency that lot-sizing techniques yield the lowest total inventory management cost under low-variability unstable demand ($VC < 0.25$).

3.2 High-variability unstable demand

In the case where demand is unstable and high variability ($VC \geq 0.25$), demand data were simulated using the normal distributions, $N(100,50^2)$, $N(100,70^2)$ and $N(100,100^2)$.

From Fig. 3, when demand is set to $N(100,50^2)$ and ordering cost $O = 20$ is considered, it is found that the WW method yields the lowest total cost in all scenarios. Among heuristic methods, when holding cost $H = 0.1$, the POQ method performs as the second-best approach. When the holding cost increases to 0.5 and 1.0, the LFL and POQ methods show improved performance and become closer to the WW method. When ordering cost $O = 50$, the WW method remains the best performing method, while LFL and POQ serve as the next best alternatives. When demand is set to $N(100,70^2)$ and ordering cost $O = 20$ is considered, the WW method again yields the lowest total cost in all scenarios. Among heuristic methods, when the holding cost $H = 0.1$, the POQ method provides the second-best performance. When the holding cost increases to 0.5 and 1.0, both LFL and POQ methods demonstrate improved efficiency and approach the results of the WW method. When ordering cost $O = 50$, the WW method remains the best, while LFL and POQ remain the second-best alternatives. Finally, when demand is set to $N(100,100^2)$ and ordering cost $O = 20$ is considered, the WW method consistently yields the lowest total cost across all scenarios. For heuristic methods, when holding cost $H = 0.1$, the POQ method again performs as the second-best method. When the holding cost increases to 0.5 and 1.0, LFL and POQ show improved performance and become closer to the WW method. When ordering cost $O = 50$, the WW method remains the best-performing approach, while LFL and POQ continue to be the next best alternatives.

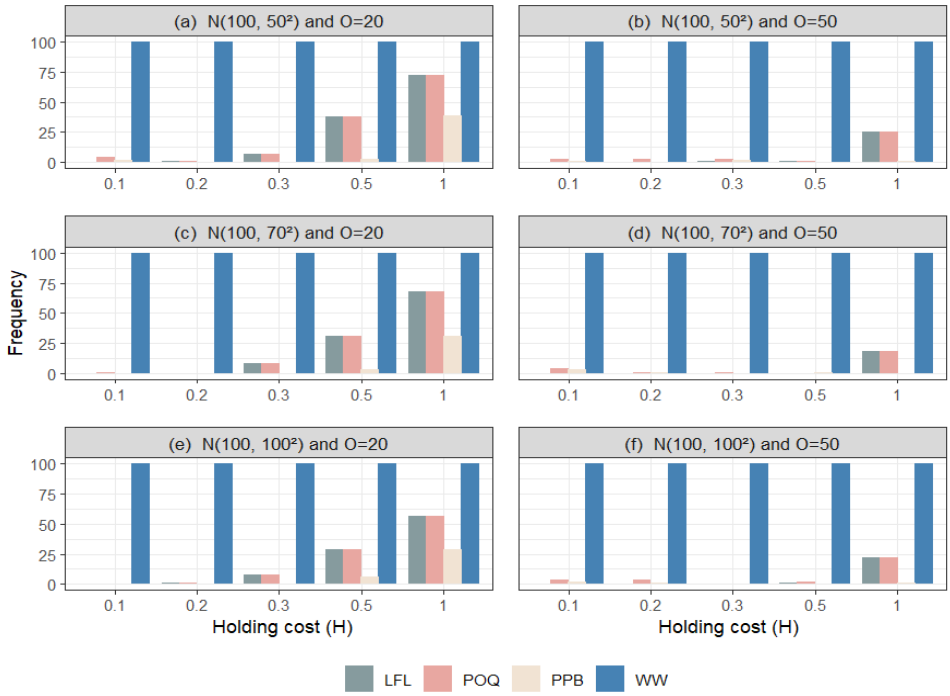


Fig. 3. Column chart the frequency that lot-sizing techniques yield the lowest total inventory management cost under high-variability unstable demand ($VC \geq 0.25$).

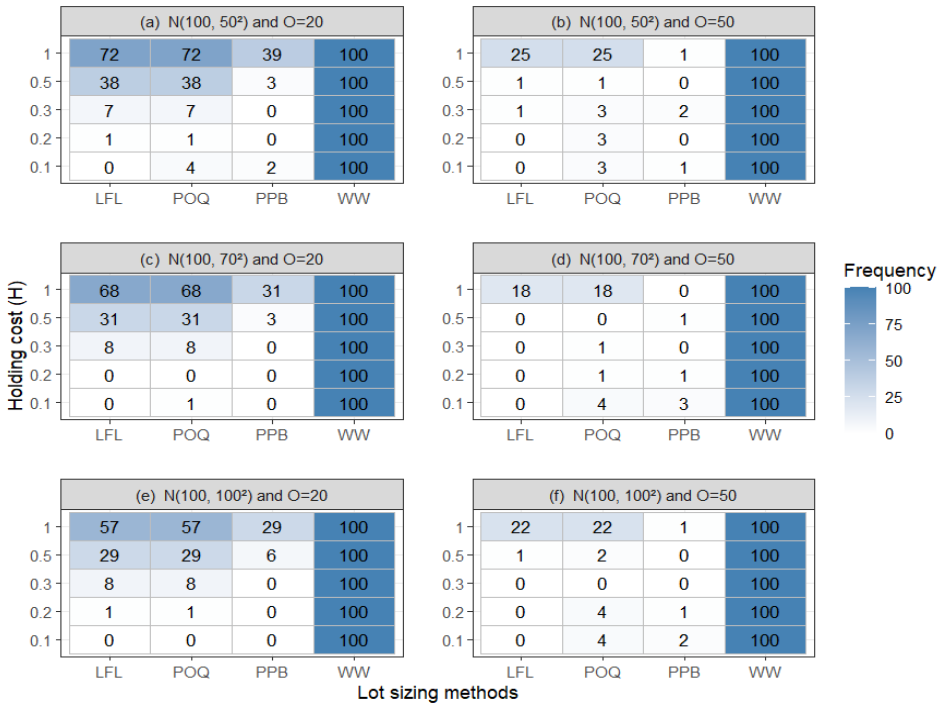


Fig. 4. Heatmap showing the frequency that lot-sizing techniques yield the lowest total inventory management cost under high-variability unstable demand ($VC \geq 0.25$).

When the ordering cost is set ($O = 20, 50$) and a comparison is made among $N(100, 50^2)$, $N(100, 70^2)$ and $N(100, 100^2)$, it is found that the WW method yields the lowest total cost in all scenarios. The performance of heuristic methods shows a clear declining trend as demand variability increases. Therefore, it can be concluded that the WW method exhibits the highest efficiency, providing the lowest total inventory management cost across all simulation scenarios (100%). In contrast, for heuristic methods under ordering costs $O = 20, 50$ and low holding cost ($H = 0.1$), the POQ method serves as the second-best alternative. However, when the holding cost increases to 0.5 and 1.0, both LFL and POQ methods show improved performance, and in some cases, become comparable to the WW method due to more frequent ordering aligned with actual demand, which helps reduce holding costs. These results are consistent with the heatmap presented in Fig. 4. Considering the average percentage of relative change between the heuristic methods and the WW algorithm, as shown in Table 2, the POQ method had the lowest value both $n = 12$ and $n = 52$, followed by the LFL method.

Table 2. Average of percent relative change between heuristics and WW algorithm.

Variability Coefficient	Demand Distribution	Number of Time Periods	Heuristic Methods			
			LFL	EOQ	POQ	PPB
$VC < 0.25$	$N(100, 10^2)$	$n = 12$	19.56%	66.81%	7.45%	258.89%
		$n = 52$	19.65%	65.78%	4.56%	979.40%
	$N(100, 30^2)$	$n = 12$	22.88%	69.23%	11.65%	278.63%
		$n = 52$	23.63%	67.77%	9.31%	1112.59%
$VC \geq 0.25$	$N(100, 50^2)$	$n = 12$	26.06%		15.06%	268.38%
		$n = 52$	28.24%		13.05%	1097.25%
	$N(100, 70^2)$	$n = 12$	26.27%		18.13%	250.10%
		$n = 52$	27.82%		14.58%	1051.12%
	$N(100, 100^2)$	$n = 12$	24.02%		19.39%	217.97%
		$n = 52$	25.39%		17.06%	938.69%

3.3 Discussion

From the results of this study on order lot-sizing under unstable demand, a comparison was conducted among different methods, including optimization-based methods using the Wagner–Whitin (WW) method, and heuristic methods, namely LFL, POQ, EOQ, and PPB, by varying demand variability, number of time periods, and cost structures. The results show that the WW method provides the lowest total inventory management cost across all scenarios (100%), both under low and high demand variability, as well as across all levels of ordering and holding costs. This can be explained by the fact that the WW method is a dynamic programming approach that explicitly considers demand in each period and can identify the global optimal solution, thereby minimizing total cost efficiently. However, the results also show that heuristic methods such as POQ and LFL can yield results that were close to the WW method in several scenarios, especially when the holding costs are high. This reflects that ordering in closer alignment with actual period demand can vitally reduce inventory holding costs. These findings are consistent with the study of Thuennadee et al. [25], which found that the WW method provides the lowest cost. Although heuristic methods yield results that are not drastically different from the optimal solution, with an average deviation of no more than 8%, they are still practically applicable in the real world.

In addition, when considering the effect of holding cost, it is found that under a low holding cost level, the POQ method tends to provide better results, as it can consolidate

orders and thereby reduce total ordering costs. However, as holding costs increase, the LFL method becomes more efficient because it orders the required quantity directly based on demand at each period, resulting in lower inventory levels. These findings are consistent with the concept of minimizing inventory holding costs and are in line with the study of Bamrungsri [26], which reported that heuristic methods can effectively reduce inventory costs in real case studies. However, the results of this study differ from those of Auansamo and Kittitheerapornchai [27], which found that the Silver-Meal method provides the most suitable solution, yielding total costs closest to those of the Wagner–Whitin method. Such differences may be attributed to variations in data characteristics and study contexts, as their research was applied to real industrial case data in a manufacturing setting, whereas this research employs simulated data under controlled conditions, which may lead to differences in the resulting solutions.

From the above discussion, it can be concluded that the WW method is the most appropriate approach in theoretical terms for determining order quantities under unstable demand. In contrast, heuristic methods such as POQ and LFL are suitable alternatives in practical applications, as they involve less complex computational procedures and can produce results that are close to those of the optimal solution method. However, in choosing the appropriate method both the characteristics of product demand and the organization's cost structure should be considered in order to achieve maximum efficiency in inventory management.

3.4 Suggestions for implementation

1) The results of this study indicate that the Wagner–Whitin (WW) method yields the lowest total inventory management cost across all scenarios. Therefore, organizations that have clearly defined demand data for each period, which is typically fluctuating or irregular over time, should consider applying this method in order planning. This would enhance inventory management efficiency and reduce overall costs.

2) In cases where an organization has limitations in computational complexity or cannot use dynamic programming models, heuristic methods such as POQ and LFL may be considered as alternatives. These methods yield results close to the optimal solution, particularly in scenarios with high holding costs.

3) When selecting an appropriate lot-sizing technique, consideration should be given to the characteristics of product demand, particularly the level of demand volatility and cost structure, including ordering costs and annual unit holding costs, because these factors have a significant impact on the effectiveness of each method.

4) It is recommended to continuously collect and analyze demand data in order to select appropriate lot-sizing techniques that are consistent with actual operating conditions at each period.

3.5 Future studies

1) To improve the efficiency of future research, the scope of planning could be expanded by increasing the number of demand periods, such as daily demand ($n = 365$), or by considering higher ordering cost levels, such as $O = 100$ or other values. This may be relevant for products with high ordering costs.

2) When simulating demand data, consider using alternative probability distributions that represent non-negative demand models, such as the truncated normal distribution, log-normal distribution, gamma distribution, or empirically calibrated count/continuous models. These may better reflect the distribution patterns of demand data for specific product types.

3) For complex situations where demand is more uncertain and volatile, implementing a dynamic lot sizing method using stochastic models in stochastic inventory policy operations is crucial. Additionally, lead times, safety stock, stockout penalties, or service levels—factors

associated with the Reorder Point (ROP) and inventory control, may be considered in models.

4) Developing a decision support system (DSS) that integrates various methodologies and automatically selects the most appropriate approach should be considered in order to improve efficiency and facilitate practical application.

4. Conclusion

This study simulates product demand scenarios and compares the efficiency of lot-sizing techniques under variable demand, using both optimization-based and heuristic approaches. Demand data was simulated as a normal distribution with a mean of 100 and various standard deviations, and the two time periods were considered: 12 periods (monthly) and 52 periods (weekly). Demand variability was categorized into two levels based on the variability coefficient (VC): low variability ($VC < 0.25$) and high variability ($VC \geq 0.25$). Each scenario was evaluated across two levels of ordering cost ($O = 20, 50$) and five levels of holding cost ($H = 0.1, 0.2, 0.3, 0.5, 1.0$). For the low demand variability, the order lot-sizing techniques analyzed included WW, LFL, EOQ, POQ, and PPB. For high demand variability, the analysis focused on WW, LFL, POQ, and PPB. The results indicate that the WW method, which is an optimization approach, yields the lowest total cost across all simulated conditions (100% of all scenarios). For heuristic methods, the POQ and LFL methods perform as the second-best approaches, particularly when holding cost is high, as both methods effectively reduce excess inventory levels. In contrast, the EOQ and PPB methods provide the best results only in certain cases, due to the limitation of their underlying assumptions, which are not fully able to capture fluctuations in demand across time periods.

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